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IKONOS Imagery to Estimate Surface Soil Property Variability in Two Alabama Physiographies

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ABSTRACT

Knowledge of surface soil properties is used to assess past erosion and predict erodibility, determine nutrient requirements, and assess surface texture for soil survey applications. This study was designed to evaluate high resolution IKONOS multispectral data as a soil-mapping tool. Imagery was acquired over conventionally tilled fields in the Coastal Plain and Tennessee Valley physiographic regions of Alabama. Acquisitions were designed to assess the impact of surface crusting, roughness, and tillage on our ability to depict soil property variability. Soils consisted mostly of fine-loamy, kaolinitic, thermic Plinthic Kandiudults at the Coastal Plain site and fine, kaolinitic, thermic Rhodic Paleudults at the Tennessee Valley site. Soils were sampled in 0.20-ha grids to a depth of 15 cm and analyzed for percentages of sand (0.05–2 mm), silt (0.002–0.05 mm), clay (<0.002 mm), citrate-dithionite extractable Fe, and total C (TC). Four methods of evaluating variability in soil attributes were evaluated: (i) kriging of soil attributes, (ii) cokriging with soil attributes and reflectance data, (iii) multivariate regression based on the relationship between reflectance and soil properties, and (iv) fuzzy *c*-means clustering of reflectance data. Results indicate that cokriging with remotely sensed (RS) data improved field scale estimates of surface TC and clay content compared with kriging and regression methods. Fuzzy *c*-means worked best using remotely sensed data acquired over freshly tilled fields, reducing soil property variability within soil zones compared with field scale soil property variability.

Surface soil properties are often used to assess soil quality, establish soil survey map units, and determine agrochemical application rates. Current soil sampling methods designed to capture field scale variability include grid-sampling and directed sampling using management zones. In a grid-sampling approach, grids are created in an attempt to assess spatial variability (Franzen and Peck, 1995). Depending on field size and variability, an accurate assessment of soil properties is best achieved through a densely sampled grid, making spatially representative estimates cost-prohibitive. While management zone (directed) sampling shows promise, representative zones are best developed over time using a combination of data layers such as yield, topography, and soil maps (Franzen et al., 1998). Newly available high-resolution satellite imagery may discriminate among differences in surface soil attributes. Methods such as cokriging soil samples with highly correlated spectra, fuzzy *c*-means clustering of remotely sensed (RS) data, and multiple linear regression relating spectral response to soil attributes may be used to evaluate variability in surface soil properties.

The basic relationships between spectral response and soil properties have been well researched. Early studies have shown a negative correlation exists between surface TC and reflectance in the visible (VIS) and near infrared (NIR) (Baumgardner et al., 1970; Sudduth and Hummel, 1991; Henderson et al., 1992). Increasing amounts of TC have a darkening effect, consequently reducing the amount of energy reflected. Similarly, Coleman and Montgomery (1987) found a strong negative correlation ($r = -0.58$) between TC and NIR (0.76–0.90 μm) reflectance in Vertisols and Alfisols in Alabama's Blackbelt region. These authors noted increasing soil water content, coincident with increasing TC, tended to depress surface reflectance and mask spectral features of interest (Johnson et al., 1998).

Soil texture also impacts soil spectral response curves. In highly weathered and eroded soil systems of the Southeastern Coastal Plain and Tennessee Valley physiographic regions, the sand (0.05–2 mm) fraction is primarily composed of quartz with lesser quantities of mica, and clay (<0.002 mm) particles consist of kaolinite, with lesser quantities of hydroxy–interlayered vermiculite, Fe oxides, and gibbsite (Shaw et al., 2002, 2003). In eroded soils, increasing clay quantities at the surface attenuate reflectance as finer particles cause scattering of energy (Mathews et al., 1973; Stoner and Baumgardner, 1981; Salisbury and D'Aria 1992). Barnes and Baker (2000) used multispectral airborne and satellite data to create surface soil texture maps for two sites at the Maricopa Research Farm in Arizona. Due to variability in soil water content, surface roughness, and residue cover between sites, RS-derived soil texture maps were most accurate when generated on a site-by-site basis. Thomasson et al. (2001) reported similar findings, which showed the relationship between spectral response and soil texture was highly variable between two farm sites in Mississippi. However, using spectra within the 0.40- to 0.80- and 0.95- to 1.05-μm ranges >50% of the variability in soil texture was explained.

Soil spectral response relative to the amount of mineral, organic, and water content has been well established. However, extrapolation to field conditions is confounded by variability in surface roughness, crop residue cover, crusting, and soil water content. Several methods show potential for improving our ability to discriminate among changes in surface soil attributes. Two of these

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Abbreviations: NIR, near infrared; PAN, panchromatic; RMSE, root mean square error; RS, remote sensing/sensed; TC, total carbon; VIS, visible.

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methods include: cokriging less-densely sampled soil attributes with highly correlated spectra and fuzzy *c*-means clustering of pixels based on differences in surface reflectance.

Geostatistical analyses that integrate high resolution RS data with measured surface properties may improve our ability to resolve finer differences among surface soil properties. Early research by Zhang et al. (1992) demonstrated that cokriging with a highly correlated covariate could be used to improve estimates of soil texture. In their study, soil samples were collected on a 100-m grid and analyzed for soil texture. Reflectance was measured using a handheld radiometer under wet and dry conditions. Results showed that cokriging reduced mean square errors by 33% using only 17 to 25% of the original soil samples. More recently, Bishop and McBratney (2001) compared statistical and geostatistical algorithms to map soil cation exchange capacity. Covariates used in this study included apparent electrical conductivity, Landsat imagery and crop yield. Results suggested that algorithms utilizing electrical conductivity or RS imagery as a covariate improved results over traditional statistics and simple kriging.

Fuzzy *c*-means is a multivariate clustering algorithm that differs fundamentally from other multivariate clustering algorithms by allowing non-normal data distributions and partial class membership. Recent studies have utilized fuzzy *c*-means to generate detailed digital soil maps by clustering physical and chemical soil properties (Young and Hammer, 2000; Triantafilis et al., 2001). However, the real potential of cluster analyses may lie in the utilization of RS imagery. Because reflectance is correlated with many soil attributes, fuzzy cluster analysis of high-resolution satellite imagery shows promise as a tool for the delineation of soil variability.

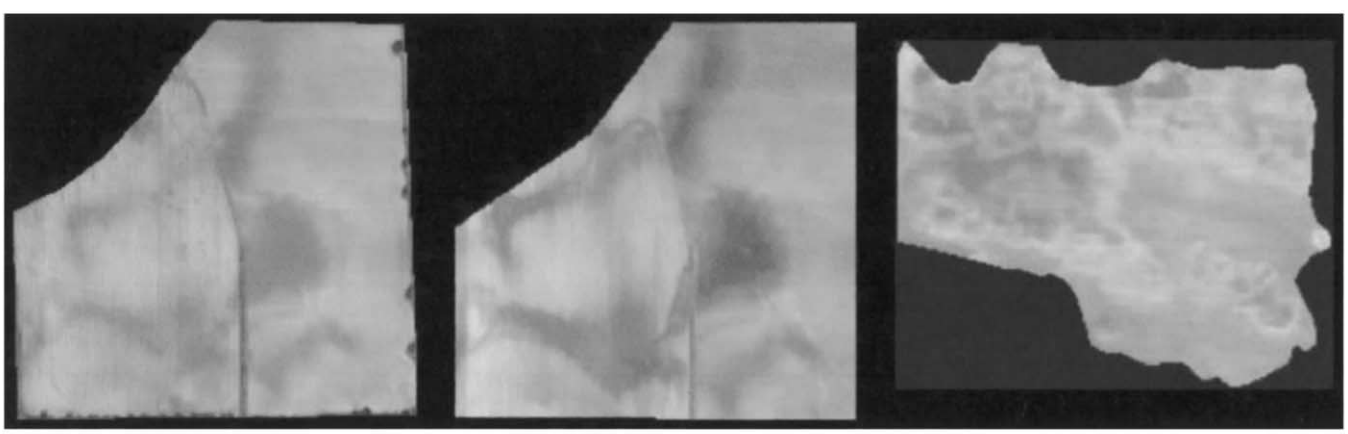
Assessment of surface soil property variability is critical to site-specific management, soil survey and natural resource inventory. However, directed soil sampling approaches have been limited in the past by researcher bias in sampling design and failure to treat the soil as a continuous surface. This study was designed to evaluate our ability to depict surface soil variability using newly available, high-resolution satellite imagery. Specifically we will: (i) investigate the utility of IKONOS multispectral satellite imagery to assess the spatial variability of surface soil properties under different tillage regimes, and (ii) evaluate the potential of three methods relating RS to soil property variability (multivariate regression, kriging, and cokriging) and one clustering-based algorithm (fuzzy *c*-means) to resolve surface soil variability.

MATERIALS AND METHODS

Study Sites

Study sites were located in two intensive agricultural regions of Alabama. The Coastal Plain study site was located on a 52-ha farm near Headland, AL (85°16′04″ W long., 34°38′14″ N lat.). The landscape is gently sloping and soils formed in sandy and loamy fluvial-marine sediments and classify mostly as fine-loamy, kaolinitic, thermic Plinthic Kandiudults. The Coastal Plain is intensively cropped to peanuts (*Arachis hypogaea*), cotton (*Gossypium hirsutum* L.), and corn (*Zea mays* L.). The second study site was located on a 31-ha farm in the Tennessee Valley near Decatur, AL (87°08′42″ W long., 34°38′49″ N lat.). This region is proximate to the Tennessee River and more steeply sloping compared with the Coastal Plain. Soils formed from limestone residuum, and classify mostly as fine, kaolinitic, thermic Rhodic Paleudults. Typical land-use practices for this region are row-cropping with cotton, corn, and wheat (*Triticum aestivum* L.).

Each site was managed as a conventionally tilled system representative of the two physiographic regions. Remote sensing acquisitions were designed to capture differences in soil attributes as well as the impact surface conditions may have on spectral reflectance (Fig. 1). Data were acquired at the Tennessee Valley site on 19 Feb. 2002. Surface conditions were rough and typical of clayey soils following fall-tillage and winter fallow. Data were acquired twice at the Coastal Plain site, 14 Feb. 2002 and 27 Mar. 2002, and designed to capture pre- and post-tillage surface conditions. This is particularly important in the sandy soils of the Coastal Plain, where surface crusting following rainfall events is common. Crusting occurs when rainfall or irrigation events mechanically breakdown and disperse soil aggregates. Dispersed clay particles set-



Pre-Tillage, Coastal Plain **Post-Tillage, Coastal Plain** **Tennessee Valley**

Fig. 1. IKONOS images displaying a false color composite of the red (0.63–0.69 μm), green (0.52–0.60 μm), and near infrared (0.76–0.90 μm) for each site and acquisition. Data were acquired on 2/14/02 (pretillage) and 3/27/02 (post-tillage) at the Coastal Plain site and 2/19/02 at the Tennessee Valley site. Data are provided as a point of comparison with cokriged and fuzzy clustering results.

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tle within pore spaces, and effectively reduce infiltration (Agassi et al., 1981) can significantly alter reflectance properties (Eshel et al., 2004; Ben-Dor et al., 2003). To evaluate the impact of surface crusting on spectral reflectance at the Coastal Plain site, the first image was acquired over a crusted surface before spring tillage, and a second image was acquired over relatively smooth, freshly tilled, cultivated soil.

Soil Analyses

Each study site was grid sampled coincident with satellite data acquisition. Soils at each site were near field capacity at the time of sampling. Soils were a composite of ten random samples (0–15 cm) within a 5-m radius of the center of each 0.20-ha grid. Samples were collected to the depth of soil mixing in conventional tillage operations. The number of soil samples per site amounted to $n = 246$ at the Coastal Plain study site and $n = 158$ at the Tennessee Valley site. Before laboratory analysis, soil samples were air dried and sieved to pass a 2-mm sieve. Analyses included total TC via dry combustion on pulverized samples (Campbell, 1992), citrate-dithionite extractable Fe (Jackson, 1975) and particle-size distribution on the <2-mm fraction (Kilmer and Alexander, 1949).

IKONOS Multispectral Scanner

The IKONOS[1] satellite (Space Imaging, Thornton, CO) orbits the earth in a sun synchronous orbit at an altitude of 681 km. The sensor on board IKONOS possesses a multispectral scanner equipped with three VIS, one NIR, and one panchromatic (PAN) band (Table 1). Visible and NIR bands acquire data with 4 m spatial resolution, and PAN data are acquired at 1-m spatial resolution. Data were collected on days having <10% cloud cover, as close to solar noon as possible.

Multispectral data were adjusted for atmospheric attenuation using an Internal Average Relative Reflectance algorithm in ERDAS Imagine[1] (Leica Geosystems, Heerbrugg, Switzerland) for each IKONOS scene. The internal average relative reflectance assumes that average scene reflectance is composed of a variety of surface attributes (vegetation, water, soil) and approximates a spectrally flat field. Internal average relative reflectance reduces spectral contributions from common variables, such as atmospheric interference, by taking a ratio of each pixel and the flat field value (ERDAS, 2002). In some cases, this can eliminate or reduce absorption features of interest (Zamudio and Atkinson, 1990). However, in practice, internal average relative reflectance has been shown to work well when certain criterion are met: (i) scene is representative of a variety of surface attributes, (ii) no significant changes in topography exist, and (iii) atmospheric properties are constant within a scene (ERDAS, 2002). Because the flat field is generated from at-sensor digital values representative of surface features and atmospheric contribution/attenuation, the internal average relative reflectance is considered an effective means of removing or reducing atmospheric effects (Kruse, 1988). Kruse (1988) successfully used this approach to compare Airborne Imaging Spectrometer data with laboratory-derived spectra of hydrothermally active rocks. Data showed that internal average relative reflectance values closely approximated laboratory spectra.

[1] Use of a particular product does not indicate the endorsement of Auburn University, the Alabama Agricultural Experiment Station, National Aeronautics and Space Administration, or the USDA Agricultural Research Service.

Table 1. Wavelength and spatial resolution for each visible (VIS), near infrared (NIR) and panchromatic bands on the IKONOS sensor.

Wavelength	Spectra	Spatial resolution
μm		m^2
0.45–0.52	VIS-blue	4
0.52–0.60	VIS-green	4
0.63–0.69	VIS-red	4
0.76–0.90	NIR	4
0.45–0.90	PAN	1

Spectral Response Curves

Spectral response curves corresponding to each RS acquisition were created to illustrate the impact of tillage regime and soil texture on observed reflectance patterns. Spectral response curves were generated for the Coastal Plain site only, since RS data were captured pre- and post-tillage. Spectral response curves for each RS acquisition represent soils having a range in clay content (5.6–29.8%) (Fig. 2).

Statistical Analysis

Statistical analyses were designed for systematic comparison of RS-based and non RS-based methods of assessing field scale TC and clay content variability. Surface TC and clay content were chosen as the variables of interest as they impact infiltration, sedimentation and aggregation, and agrochemical application rates/placement. Four methods of analysis were chosen: kriging, cokriging, multivariate regression, and fuzzy *c*-means clustering.

Correlation

Before cokriging, multivariate regression, and fuzzy *c*-means clustering, the correlation between spectral response and soil attributes was evaluated. Remotely sensed data were extracted using a 5-m buffer around all geospatially attributed sample locations and correlated with measured TC and clay content ($p < 0.05$). Next, highly correlated bands were selected as input for cokriging, multivariate analyses, and fuzzy *c*-means clustering.

Kriging

Kriging was chosen as a non-RS based method. Based on spatial covariance properties, kriged maps of TC and clay content were generated for each site using measured TC and clay content from grid sampled locations. Unlike RS-based meth-

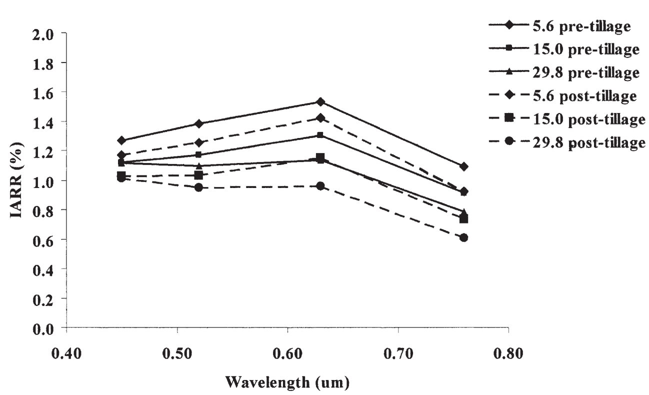

Fig. 2. Spectral response curves constructed using sampling points ($n = 10$) that correspond to soils having increasing percentages of surface clay (5.6, 15.0, and 29.8%) content at the Coastal Plain study site. Data were acquired on 2/14/02 (pretillage) and 3/27/02 (post-tillage). Reflectance was reported as Internal Average Relative Reflectnace (IARR).

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Table 2. Semivariogram parameters for surface total carbon (TC), clay, and remotely sensed data at the Tennessee Valley and Coastal Plain study sites. Nugget semivariance, range, and r^2 are reported for each variate, covariate and cross covariance.

Site	Method	Variate	Covariate	Range	Nugget semivariance	r^2
				m	%	
Tennessee Valley	Kriging	TC	–	822.9	20.73	0.96
	Cokriging	–	Red	292.8	47.85	0.89
	Cokriging	TC	Red	263.8	9.60	0.97
	Kriging	Clay	–	228.0	23.57	0.97
	Cokriging	–	Green/Red	154.1	10.85	0.86
	Cokriging	Clay	Green/Red	263.8	1.33	0.97
Coastal Plain (Pretillage)	Kriging	TC	–	192.4	6.93	0.98
	Cokriging	–	NIR	163.0	1.62	0.99
	Cokriging	TC	NIR	186.8	2.43	0.98
	Kriging	Clay	–	197.6	0.01	0.98
	Cokriging	–	Green	188.7	7.15	0.99
	Cokriging	Clay	Green	200.4	2.11	0.96
Coastal Plain (Post-tillage)	Kriging	TC	–	192.4	6.93	0.98
	Cokriging	–	NIR	155.3	0.04	0.99
	Cokriging	TC	NIR	180.8	0.20	0.98
	Kriging	Clay	–	197.6	0.01	0.98
	Cokriging	–	Green	176.3	0.04	0.99
	Cokriging	Clay	Green	192.4	0.18	0.94

ods, kriged maps are independent of surface conditions at the time of sampling.

Before kriging, 10% of the sample points were randomly selected and retained for accuracy assessments. Using the remaining sample points, the spatial structure of each dataset was evaluated via isotropic and anisotropic semivariograms. Semivariograms constructed for each variate were well structured with minimal anisotropy. Semivariograms were best represented using the spherical model. Spatial dependence was estimated via nugget semivariance, which represents the percentage of nugget (unexplained variance) compared with the total variability accounted for in the semivariogram (nugget + sill). Nugget semivariances <25% indicate strong spatial dependence while nugget semivariance >75% are weakly spatially dependent (Cambardella et al., 1994). In all cases, RS and soil data exhibited moderate to strong spatial dependencies with correlation ranges between 154 to 293 m (Table 2).

Interpolated maps of TC and clay content were generated using block kriging at 4-m resolution. Block kriging was chosen because sampled locations were considered representative of an area (5-m radius). Using soil samples retained for accuracy assessments, root mean square errors (RMSE) were calculated between measured and interpolated values of TC and clay content at each site. Distribution of the residuals was examined to identify any bias in interpolated estimates.

Cokriging

Cokriging is a hybrid interpolation procedure, which takes advantage of the correlation between a secondary, more intensely sampled variable, and the primary variate (Zhang et al., 1992). In this study, high-resolution RS data were used as the secondary variate. Since spectral response has been shown to vary with surface roughness, crusting, and soil water content (Coleman and Montgomery, 1987; Johnson et al., 1998), cokriging was chosen to evaluate whether RS data paired with measured soil attributes could be used to reduce the uncertainty in our ability to resolve soil property variability.

Using the same random selection of points as defined for kriging, new data sets were created by assigning georeferenced soil data to the corresponding RS image(s) in a geographic information system. In our case, new data sets comprised the February 19 RS acquisition at the Tennessee Valley site, the February 14 RS acquisition at the Coastal Plain site, and the March 27 RS acquisition at the Coastal Plain site. Covariates were chosen by selecting the band or band ratio that was most highly correlated ($P < 0.05$) with each soil property. For each of the new datasets, isotropic, and anisotropic semivariograms for each variate, covariate, and cross-covariation were evaluated. All data showed well-structured isotropic semivariance and were analyzed using the spherical model. Nugget semivariances were also calculated to evaluate the degree of spatial dependence for each soil property, corresponding covariate, and cross covariance.

Next, interpolated maps of TC and clay content were generated using block cokriging. Pixel sizes were set to 4-m to correspond with the spatial resolution of the RS imagery. Similar to the above, RMSEs were calculated between measured and interpolated values of TC and clay content at each site and residual distributions evaluated.

Multivariate Regression

Multiple linear regression analyses between RS data and TC or clay content were evaluated as a nongeospatial technique. Multivariate regression was based on the relationship between spectral response and TC or clay at a point, thus data are not treated as a continuous surface and the spatial covariation between points is ignored.

A 5-m buffer around each soil point was used to extract internal average relative reflectance data from each image. A random selection of 10% of the points were removed and retained for accuracy assessments. Using the remaining sample points, multiple linear regression analyses were performed using the NIR and three VIS bands, along with the green to red band ratio [(0.52–0.60 μm)/(0.63–0.69 μm)], which was correlated with clay content ($r = 0.47$) at the Tennessee Valley site. A variance inflation factor was included in the regression analyses to systematically remove spectra that were highly correlated with each other. Using the multiple linear regression equations generated for each dataset, estimates of TC and clay were calculated using data retained for the accuracy assessment. Estimated versus measured TC and clay contents were used to calculate RMSEs and residual distributions.

Fuzzy *c*-Means

Remotely sensed data for each acquisition were clustered using a multivariate fuzzy *c*-means algorithm (Fridgen et al., 2000). This approach requires the least amount of a priori input compared with kriging, cokriging, and multivariate regression. Because fuzzy *c*-means clustering is designed to handle nonnormal data distributions and allow partial class membership,

Table 3. Pearson's correlation coefficients ($p < 0.05$) relating remotely sensed IKONOS data to surface (0–15 cm) total carbon (TC) and clay content at the Tennessee Valley and Coastal Plain study sites.

Site	Acquisition	Soil property	IKONOS Bands, *r* 0.76–0.90	0.63–0.76	0.52–0.60	0.52:0.63
			μm			
Tennessee Valley	2/19/02	TC	−0.25	−0.31	−0.29	0.21
		Clay	−0.20	−0.12	−0.45	0.47
Coastal Plain	2/14/02	TC	−0.39	−0.23	−0.20	0.26
		Clay	−0.52	−0.54	−0.61	0.18
Coastal Plain	3/27/02	TC	−0.75	−0.73	−0.71	0.78
		Clay	−0.57	−0.53	−0.58	0.47

it is an ideal approach for landscape or field-scale assessments (Fridgen et al., 2004).

Remotely sensed variables most highly correlated with TC and clay content were chosen as input into the multivariate clustering algorithm. For each site, the two spectral bands most highly correlated with TC and clay content were chosen. A single RS acquisition at the Tennessee Valley site showed that red (0.63–0.69 μm) spectra for TC and the green to red band ratio for clay content were best correlated (Table 3). In the Coastal Plain, two RS data sets were evaluated. Analyses showed that for both RS acquisitions the green and NIR spectra were best correlated with clay and TC, respectively. Before clustering, the variance and covariance for each spectral band were assessed to determine the most appropriate clustering technique. Because spectral data for each field exhibited unequal variances with covariance values greater than zero, the Mahalanobis Distance Method was used to delineate clusters. A fuzziness threshold of 1.3 was assigned as suggested by Fridgen et al. (2004) for soil surfaces.

The clustering software, Management Zone Analyst (Fridgen et al., 2004), generates two performance indices as a metric of the organization gained with each additional cluster. Each method ranges in value from 0 (highly organized) to 1 (disorganized). Performance indices indicated that the Tennessee Valley site was best organized into three zones, while the Coastal Plain site was best organized into two zones pretillage and four zones post-tillage. To evaluate the performance of the *c*-means clustering, the coefficient of variation (CV) was calculated for all measured soil properties (TC, sand, silt, and clay) across the field and within delineated soil zones.

RESULTS AND DISCUSSION

Soil Attributes

Surface soil properties at each site were representative of two distinct physiographic provinces within the state of Alabama, differing in sand, silt, clay, citrate-dithionite extractable Fe, and TC content (Table 4). Soils collected at the Coastal Plain study site were predominantly sandy loam and loamy sand textured, with a mean sand content of 75.8% (±8.6). Lesser amounts of silt (13.1% ± 0.3), clay (11.2% ± 4.2), and Fe (0.57 ± 0.21) were found. Tennessee Valley soil samples had higher quantities of silt (46.2% ± 1.0), clay (19.7% ± 7.7), and Fe (1.50 ± 0.69) with lower amounts of sand (33.6% ± 0.8). Differences in TC content were less substantial between sites with slightly greater TC at the Coastal Plain (0.60% ± 0.32) compared with the Tennessee Valley (0.49% ± 0.22).

Spectral Relationships

Spectral response curves before and after a tillage event at the Coastal Plain site showed reflectance patterns associated with texture and surface conditions at the time of RS data acquisition. The shapes of the spectral response curves were consistent between tillages, with differences primarily in the magnitude of response (Fig. 2). Pre- and post-tillage spectral response curves showed that surface soils with a higher clay content caused a corresponding decrease in reflectance. This is in agreement with previous research, which shows soil reflectance curves are positively related to soil particle size as finer particles cause scattering of light (Mathews et al., 1973; Stoner and Baumgardner, 1981; Salisbury and D'Aria, 1992). Differences in the magnitude of reflectance between tillage events provided evidence that surface conditions, particularly crusting, substantially impacts the magnitude of reflectance. Our data showed surfaces were most reflective before tillage, which is not surprising given that these sandy soils are prone to surface crusting. Essentially, rainfall or irrigation between tillage events slowly detaches silt- and clay-size particles from quartz grains. Over time these particles fill pore spaces, leaving the more reflective quartz grains exposed.

Correlation

Soil properties were best correlated with spectral response at the Coastal Plain (Table 3). A negative linear relationship existed between clay content and all spectral bands, peaking at 0.52 to 0.76 μm ($r = -0.61$, $p <$ 0.05). This relationship was consistent between tillage events. Earlier research has shown a similar pattern of decreasing spectral reflectance with increasing percentage of surface clay content, which is likely associated with a corresponding increase in the water holding ca-

Table 4. Near-surface (0–15 cm) total carbon (TC), sand, silt, clay, and citrate dithionite extractable iron (Fe_d) content at the Coastal Plain and Tennessee Valley study sites. Standard deviations are given in parentheses.

Site	Sample	TC	Sand	Silt	Clay	Fe_d
		%				
Tennessee Valley	148	0.49 (0.22)	34.1 (9.6)	46.2 (1.0)	19.7 (7.7)	1.50 (0.69)
Coastal Plain	246	0.60 (0.32)	75.8 (8.6)	13.1 (0.3)	11.2 (4.2)	0.57 (0.21)

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pacity of finer soils (Mathews et al., 1973; Stoner and Baumgardner, 1981; Salisbury and D'Aria, 1992). As previously reported by Stoner and Baumgardner (1981), our data also show that TC content was negatively correlated with reflectance peaking in the 0.63 to 0.76 μm ($r = -0.75$, $p < 0.05$) region. The correlation between TC and spectra was best following spring tillage.

At the Tennessee Valley study site, a similar trend was observed with correlation coefficients peaking at 0.63 to 0.76 μm for TC ($r = -0.31$), and the green to red band ratio for clay ($r = 0.47$). Compared with the Coastal Plain site, the correlation between soil properties and spectral response were much lower in the Tennessee Valley. At the Tennessee Valley site, rough surface conditions typical of a clayey soil following fall tillage may have contributed to the low correlation between spectral response and clay content observed. Specifically, reflectance typically decreases with increasing roughness due to shadowing and scattering of light (Matthias et al., 2000). Conversely, at the Coastal Plain site, sandier surfaces were relatively smooth following tillage.

Kriging

Total Carbon

At the Tennessee Valley site, kriged estimates of TC content resulted in a RMSE between predicted versus measured TC content = 0.11% (Table 5). The RMSE for kriged estimates of TC at the Coastal Plain was relatively higher compared with the Tennessee Valley (RMSE = 0.22% TC). At both sites, a comparison of predicted versus measured TC showed a tendency to overestimate TC at contents <0.60%. In these highly weathered systems under conventional tillage management, TC contents are generally low, so this type of error could disproportionably impact kriged estimates of TC.

Clay

At the Tennessee Valley site, kriged estimates of clay content resulted in a RMSE = 5.03%. Nugget semivariance estimates at the Tennessee Valley site suggest only a moderate spatial relationship exists (nugget semivariance = 23.57%). A much stronger spatial relationship was observed for clay contents at the Coastal Plain site (nugget semivariance = 0.01%), resulting in a lower RMSE compared with the Tennessee Valley (RMSE = 2.05% clay).

Cokriging

Total Carbon

Cokriging TC with red spectra improved estimates by 0.07% (absolute) compared with ordinary kriged estimates at the Tennessee Valley site (Table 5). Spatial dependence (nugget semivariance = 9.6%) increased with the incorporation of red spectra and contributed to the low observed RMSE (Tables 2 and 5). In an earlier study, Odeh et al. (1995) also demonstrated that cokriging soil properties with an intensely sampled covariate (digital elevation data, 10-m spatial resolution) provided the most accurate estimation of soil properties compared with kriging and regression-kriging. Using high resolution IKONOS imagery in this study, we were able to discriminate among small differences in TC content at a finer spatial resolution (4 m).

Table 5. Root mean square error (RMSE) analyses for estimated total carbon (TC) and clay content at the Tennessee Valley and Coastal Plain sites. Results are reported for kriging (KRG), and cokriging (CK), and multiple linear regression (MLR).

	RMSE		
	KRG	CK	MLR
	%		
		Tennessee Valley, 2/19/2002	
Clay	5.03	0.02	3.33
TC	0.11	0.04	0.11
		Coastal Plain, 2/19/2002	
Clay	2.05	4.02	2.18
TC	0.22	0.02	0.24
		Coastal Plain, 3/27/2002	
Clay	–†	0.84	2.42
TC	–	0.07	0.14

† Denotes missing RMSE for the kriged data set at the Coastal Plain study site on 3/27/02. Because kriging is independent of remotely sensed data, kriged estimates of soil properties were calculated only one time.

For both RS acquisitions at the Coastal Plain site, cokriging TC with correlated NIR spectra ($r = -0.39$–0.75, pre- and post-tillage respectively) increased the spatial dependency of the data and reduced uncertainty in estimated TC content by as much as 0.20% (absolute) compared with kriged estimates (Tables 2 and 5). Considering the low range in TC reported this is a significant improvement in our ability to estimate TC content. Atkinson et al. (1994) showed that despite a weak correlation between RS data and green leaf area index and pasture biomass, cokriging with RS data greatly improved estimates of green leaf area index and pasture biomass. Our results indicate that even with a low correlation between TC and RS data (as low as $r = -0.39$) a stronger spatial structure and improved estimates of TC content were obtained. This is particularly important in these highly weathered soil systems with a low range in TC content (<1.0%) (Table 4).

Clay

At the Tennessee Valley site, cokriged estimates of clay content were an improvement over kriging, lowering RMSEs by nearly 5% (absolute) (Table 5). Nugget semivariances showed that incorporation of correlated RS data ($r = 0.47$, $p < 0.05$) improved spatial dependence (Table 2). The impact of this correlation was evidenced via the strong 1:1 correlation between predicted and observed clay contents (Fig. 3). Our results indicate that cokriged maps provided more detail and better discriminated among small differences in clay content (clay = 19.7% ± 7.7). Zhang et al. (1992) compared kriging and cokriging with remotely sensed data to delineate soil particle-size distributions and found that cokriging could reduce RMSEs by as much as 33%. In their study, soil samples were dried and sieved (2 mm)

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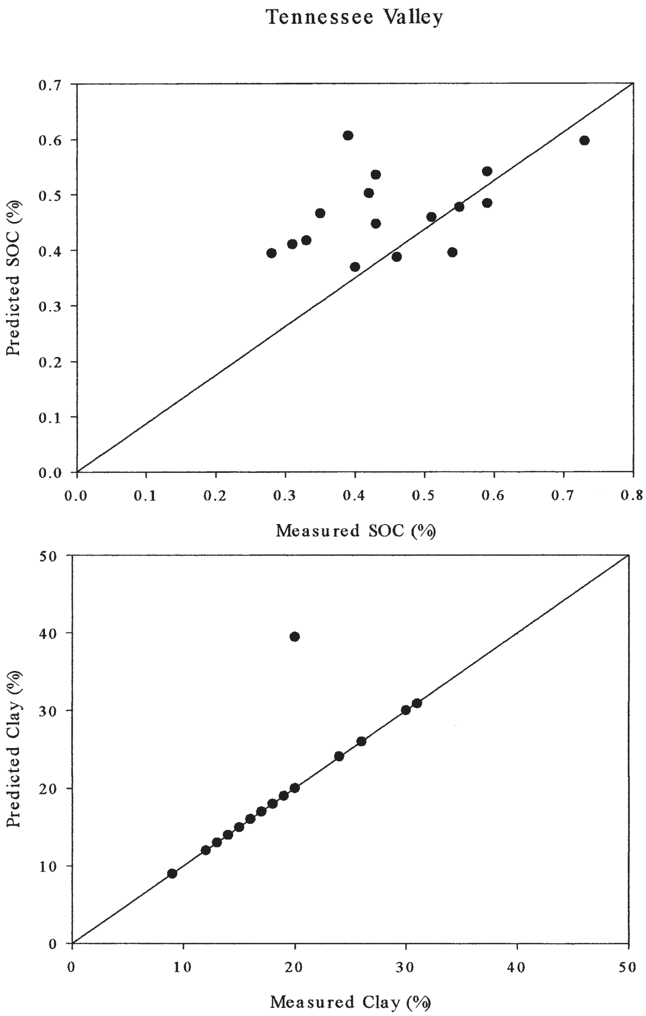

Fig. 3. Predicted (y axis) versus measured (x axis) values of total C (TC) and clay content at the Tennessee Valley study site. Predicted values were generated via kriging.

before acquiring reflectance measurements using a handheld radiometer. Their results suggest that accurate, cokriged estimates of particle-size distributions could be obtained using only 17 to 25% of the original sampling points. Results from our study indicate that field-scale applications of co-kriging clay contents with high resolution RS data can be used to produce accurate estimates of clay content variability at 4-m resolution. Future research is necessary to determine the minimum number of soil samples required to obtain accurate estimates of clay content using this approach.

Data from the Coastal Plain demonstrate that surface crusting impacts our ability to use RS data as a tool for predicting soil property variability. While cokriging produced reasonable estimates of clay content using RS data acquired pre- and post-tillage, only post-tillage cokriging improved estimated clay contents compared with kriging. Conditions before tillage, including crusted surfaces (Ben-Dor et al., 2003; Eshel et al., 2004), likely contributed to the higher RMSE observed (Table 5). Eshel et al. (2004) investigated the relationship between spectral response and crust permeability using a handheld spectroradiometer measuring reflectance in the 400- to 2400-nm range. Their study showed that reflectance from crusted surfaces was significantly greater than noncrusted surface throughout the 400- to 2400-nm range.

Following spring tillage and soil mixing at the Coastal Plain site, our data indicate that reflectance more accurately depicts soil texture. In fact, the observed RMSE for cokriged clay estimates following tillage decreased from 4.0 to 0.8%.

Multiple Linear Regression

Multiple linear regression analyses were used to relate RS data to soil properties. At the Coastal Plain site, regression estimates explained 11 to 61% of the variability in TC content using primarily red and NIR spectra pre- and post-tillage (Table 6). Estimates of clay content using RS data explained 34 to 55% of the variability. At the Tennessee Valley, regression estimates accounted for 38 to 39% of the variability in clay and TC content, respectively (Table 6).

Given the inherently low levels of TC at each site, spectral response was likely a function of mineral soil properties. At the Coastal Plain site, sandy epipedons were predominantly composed of quartz, with lesser quantities of clay. This was observed via higher reflectance in the VIS and NIR relative to decreasing proportions of clay content (Fig. 2). However, the Tennessee Valley was characterized by clayey surfaces and nearly three times the amount of surface Fe content compared with the Coastal Plain. Baumgardner et al. (1970) and Al-Abbas et al. (1972) suggest that Fe and Manganese can mask C spectra in soils having <2% TC content. In our case, the relationship between spectral response and TC was $r^2 = 0.38$, suggesting that rough surface conditions may have been the primary limitations in our ability to estimate TC in soils having <1% TC content.

Table 6. Stepwise linear regression parameters ($p < 0.05$) used to estimate near surface (0–15 cm) soil properties via remotely sensed data at the Tennessee Valley and Coastal Plain study sites. Data are reported for pre- and post-tillage conditions at the Coastal Plain site. Remotely sensed data are defined as green (0.52–0.60 μm), red (0.63–0.69 μm), near infrared (NIR)(0.76–0.90 μm), and a green/red band ratio.

Site	Soil property	Regression equation	r^2
Tennessee Valley	TC	$y = -58.85(\text{NIR}) + 45.20(\text{Green}) + 2.50$	0.39
	Clay	$y = 12.00(\text{NIR}) + -31.1(\text{Green}) + 41.1$	0.38
Coastal Plain			
Pretillage	TC	$y = -3.08(\text{NIR}) + 1.32(\text{Green}) + 1.7$	0.61
	Clay	$y = -16.1(\text{Green}) + 30.6$	0.34
Post-tillage	TC	$y = -0.23(\text{Red}) + 0.96$	0.11
	Clay	$y = -18.1(\text{Red}) + -118.8\ (\text{Green/Red}) + 151.8$	0.55

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The regression equations reported here reflect conditions specific to the site conditions at the time of RS acquisition. This is consistent with previous studies, which showed that differences in surface conditions between sites (residue cover, soil water content, vegetation) confounded results (Thomasson et al., 2001; Barnes and Baker, 2000). Thus, accurate estimates of surface soil properties via multiple linear regression analysis would require ground truthing proximate to RS data acquisition.

Total Carbon

At the Tennessee Valley site, regression estimates of TC resulted in a RMSE = 0.11% (Table 5). Analysis of residual distributions showed a strong tendency to underestimate at low TC contents and overestimate at higher TC contents (Fig. 4). A comparison of kriged, cokriged, and multiple linear regression RMSEs suggests that only cokriged estimates provided sufficient accuracy to estimate TC content under the conditions assessed at the Tennessee Valley site.

Regression estimates of TC content for the Coastal Plain site were dependent on surface conditions at the time of RS data acquisition. Total C estimates generated from RS data acquired before spring tillage typically overestimated TC, having a RMSE = 0.24%. Post-tillage estimates were less biased, and the RMSE was reduced to 0.14% (Table 5). This is equivalent to a 0.07% (absolute) increase in estimated TC compared with cokriging with NIR spectra.

Clay

Multiple linear regression improved estimates of clay content by nearly 2% (absolute) compared with kriged estimates at the Tennessee Valley site. However, when comparing multiple linear regression and cokriged datasets, cokriging provided the most accurate estimates of clay content despite rough surface conditions at the time of RS acquisition (Table 5).

Estimated clay content at the Coastal Plain site resulted in RMSEs ranging from 2.2 to 2.4% using pre- and post-tillage RS data, respectively. Pretillage, multiple linear regression resulted in lower RMSEs compared with cokriging. However, using post-tillage RS data, cokriged estimates resulted in the lowest overall RMSE (Table 5).

Generally speaking, our results are consistent with previous findings, which show cokriging soil properties with RS data provide the most accurate estimates of soil variability compared with kriging and multiple linear regression (Odeh at al, 1995; Bishop and McBratney, 2001). Bishop and McBratney (2001) also noted, as reported here, that multiple linear regression resulted in similar RMSEs compared with kriged estimates of TC and clay. However, our data provide evidence that the spatial correlation between two correlated variables (TC or clay content and RS data) can be used to improve estimates of soil property variability. Specifically, the correlation between soil properties and spectral response successfully reduced errors associated with rough surface conditions at the time of RS acquisition.

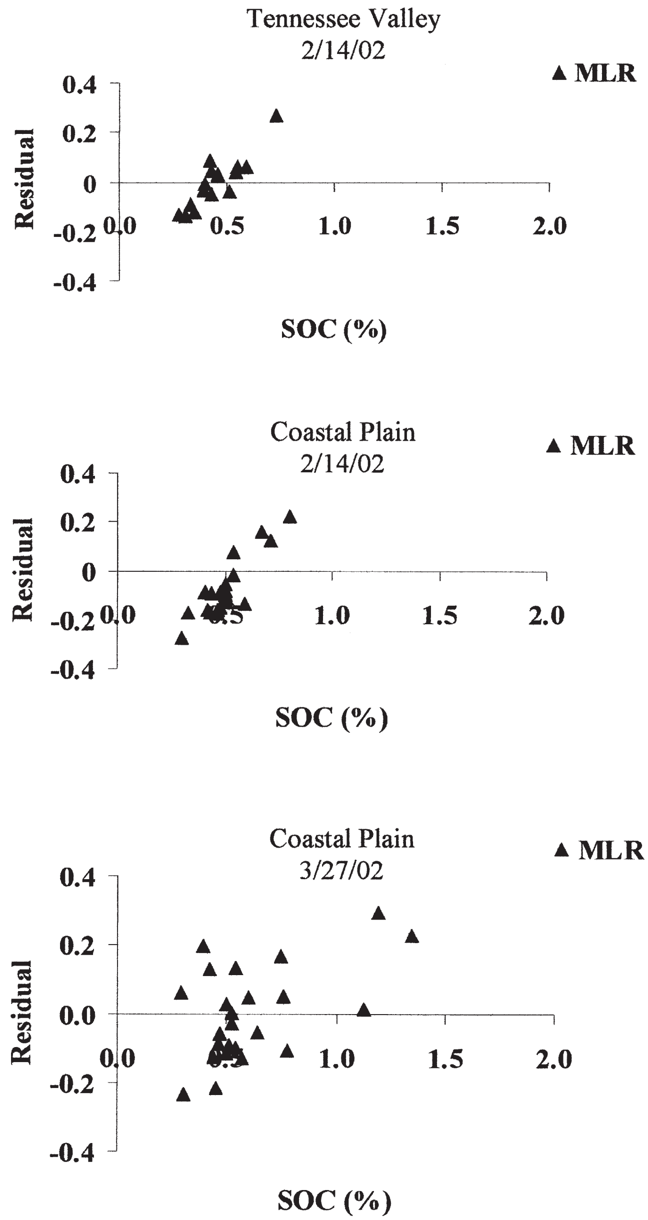

Fig. 4. Distribution of residuals obtained from multiple linear regression estimates of total C (TC) content using remotely sensed data acquired at the Coastal Plain and Tennessee Valley sites.

Fuzzy *c*-Means

At the Tennessee Valley study site, fuzzy *c*-means clustering of RS data resulted in three soil zones. Using the overall field CV for each soil property as a benchmark, our data showed that fuzzy clustering reduced the variability in clay and TC content within each zone compared with the overall field CV. Clustering did not reduce variability in silt or sand content, having CVs ranging from 14 to 32% (Table 7). With the exception of zone two, soil property variability (TC and soil texture) within each zone was >22%, possibly limiting the usefulness of the technique in this region for directed soil sampling or precision management.

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Table 7. Analysis of soil variability as delineated by fuzzy *c*-means clustering of remotely sensed data acquired at the Tennessee Valley and Coastal Plain study sites. Data are reported for pre- and post-tillage conditions at the Coastal Plain study site. Means and coefficients of variation (CV) for surface (0–15 cm) total carbon (TC), sand, silt, and clay content are give by field (All) and soil zone.

		Sand		Silt		Clay		TC	
Site	Zone	Mean	CV	Mean	CV	Mean	CV	Mean	CV
Tennessee Valley	1	33.6	32.3	48.9	23.1	17.5	36.8	0.49	28.57
	2	28.0	−18.0	44.2	−13.8	17.8	−23.7	0.40	33.71
	3	28.0	30.8	43.5	25.0	28.6	31.7	0.50	21.95
	all	34.1	29.8	46.2	22.2	19.7	39.7	0.49	45.72
Coastal Plain pretillage	1	79.6	5.3	11.1	27.7	9.3	23.7	0.49	33.62
	2	70.3	16.0	15.4	39.9	14.2	38.1	0.75	61.27
	all	75.8	11.7	13.1	39.8	11.2	38.0	0.60	55.15
Coastal Plain post-tillage	1	58.3	17.6	23.1	21.7	18.3	31.0	1.27	31.93
	2	79.7	5.5	10.8	27.5	9.5	28.1	0.47	28.06
	3	75.6	6.1	13.1	22.3	11.3	23.0	0.62	27.85
	4	79.4	4.2	10.7	17.3	10.5	25.6	0.40	25.06
	All	75.8	11.7	13.1	39.8	11.2	38.0	0.60	55.15

At the Coastal Plain site, clustering results were dependent on field conditions at the time of RS acquisition. Remotely sensed data acquired before spring tillage grouped pixels into two soil zones. Using the overall field CV for each soil property, the variability in soil properties was substantially reduced in zone one only (Table 7). Clustering with post-tillage RS data at the Coastal Plain site resulted in four soil zones. As the number of allowable classes was increased to four, the variability in soil properties in zones two through four substantially decreased compared with the overall field CV for each soil property.

Analysis of the post-tillage Coastal Plain clustering indicates that TC and clay content played a major role in soil zone delineation. Average TC and clay contents within zones differed substantially (Table 7). Total C content, for example, ranged from 1.27, 0.47, 0.62, and 0.40% in soil zones one through four, respectively. A similar trend was observed for clay, with clay contents ranging from 9 to 18% in zones 1 through 4. Compared with the field average clay content of 11%, these differences are noteworthy.

Our clustering results compare well with previous studies, and suggest that in freshly tilled soils clustering accurately depicts TC and clay variability. Ahn et al. (1999) reported similar results using hyperspectral remotely sensed data to evaluate soil property variability via linear mixing, block kriging and fuzzy *c*-means. Results showed fuzzy *c*-means clustering with RS data successfully delineated soil variability. More recently Fridgen et al. (2000) evaluated the utility of the fuzzy *c*-means algorithm using electrical conductivity and topography to evaluate the impact of landscape variability on grain yield. Data were grouped into four or five distinct clusters and explained from 10 to 35% of the variability in yield response.

CONCLUSIONS

In our study, we compared two RS-based interpretation algorithms and one non RS-based algorithm as tools to delineate soil property variability. In nearly all cases, cokriging with correlated RS imagery reduced the impact of surface conditions (roughness and crusting) and resulted in the most accurate estimates of TC and clay content. Fuzzy *c*-means was used to cluster pixels using RS data. Fuzzy *c*-means most effectively clustered RS data over freshly tilled fields in the Coastal Plain site. Rough surface conditions at the Tennessee Valley site and crusted surfaces before tillage at the Coastal Plain site limited the utility of fuzzy *c*-means clustering. Thus, clustering or cokriging with a correlated covariate may be used to provide high spatial resolution maps of soil property variability and facilitate soil survey mapping, precision agriculture, and natural resource inventories.

Our results show that satellite based estimates of soil property variability work best in conventionally tilled systems following spring tillage. In the future, as conservation tillage practices become more common, research must address the extension of this work to measure indirect indicators of soil property variability, such as, yield, cover crop vigor, and distribution of crop residue coverage proximate to planting. Keeping this in mind, in the Southeastern Coastal Plain it is common practice for peanut producers to clean till peanut fields. Considering that many row crop producers are in a cotton-peanut rotation, satellite remote sensing shows promise as a tool for the rapid assessment of soil property variability over large areas in the Southeastern Coastal Plain.

REFERENCES

Al-Abbas, A.H., P.H. Swain, and M.F. Baumgardner. 1972. Relating organic matter and clay content to multispectral radiance. Soil Sci. 114:477–485.

Agassi, M.J., I. Shainberg, and J. Morin. 1981. Effect of electrolyte concentration and soil sodicity on the infiltration rate and crust formation. Soil Sci. Soc. Am. J. 45:848–851.

Ahn, C.W., M.F. Baumgardner, and L.L. Biehl. 1999. Delineation of soil variability using geostatistics and fuzzy clustering analyses of hyperspectral data. Soil Sci. Soc. Am. J. 63:142–150.

Atkinson, P.M., R. Webster, and P.J. Curran. 1994. Co-kriging with airborne MSS. Remote Sens. Environ. 50:335–345.

Baumgardner, M.F., S.J. Kristof, C.J. Johannsen, and A.L. Zachary. 1970. Effects of organic matter on the multispectral properties of soil. Proc. Indiana Acad. Sci. 79:413–422.

Barnes, E.M., and M.G. Baker. 2000. Multispectral data for mapping soil texture: Possibilities and limitations. Appl. Eng. Agric. 16:731–741.

Ben-Dor, E., N. Goldshleger, Y. Benyamini, M. Agassi, and D.G.

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Blumberg. 2003. The spectral reflectance properties of soil structural crusts in the 1.2- to 2.5-μm spectral region. Soil Sci. Soc. Am. J. 67:289–299.

Bishop, T.F.A., and A.B. McBratney. 2001. A comparison of prediction methods for the creation of field-extent soil property maps. Geoderma 103:149–160.

Cambardella, C.A., T.B. Moorman, J.M. Novak, T.B. Parkin, D.L. Karlen, R.F. Tuco, and A.E. Konopka. 1994. Field-scale variability of soil properties in Central Iowa soils. Soil Sci. Soc. Am. J. 58: 1501–1511.

Campbell, C.R. 1992. Plant analysis and reference procedures for the southern region of the United States. Southern Coop. Ser. Bull. 368. The Georgia Agricultural Experiment Stations College of Agricultural and Environmental Sciences, Athens, GA.

Coleman, L., and O.L. Montgomery. 1987. Soil moisture, organic matter, and iron content effect on the spectral characteristics of selected vertisols and alfisols in Alabama. Am. Soc. Photogramm. 53: 1659–1663.

ERDAS. 2002. ERDAS Imagine 8.6 Online Manuals. Leica Geosystems GIS & Mapping, LLC, Atlanta, GA.

Eshel, G., G.J. Levy, and M.J. Singer. 2004. Spectral reflectance properties of crusted soils under solar illumination. Soil Sci. Soc. Am. J. 68:1982–1991.

Franzen, D.W., and T.R. Peck. 1995. Field soil sampling density for variable rate fertilization. J. Prod. Agric. 8:568–574.

Franzen, D.W., A.D. Halvorson, J. Krupinsky, V.L. Hofman, and L.J. Cihacek. 1998. Directed sampling using topography as a logical basis. p. 1559–1568. *In* P.C. Robert et al. (ed.) Precision Agriculture, Proc. Of the 4th International Conference, St Paul, MN. 19–22 July. 1998. ASA, CSSA, and SSSA, Madison, WI.

Fridgen, J.J., C.W. Fraisse, N.R. Kitchen, and K.A. Sudduth. 2000. Delineation and analysis of site-specific management zones. p. 402–410. *In* Second International Conference on Geospatial Information in Agriculture and Forestry, Lake Buena Vista, FL. 10–12 Jan. 2000.

Fridgen, J.J., N.R. Kitchen, K.A. Sudduth, S.T. Drummond, W.J. Wiebold, and C.W. Fraisse. 2004. Management zone analyst (MZA): Software for subfield management zone delineation. Agron. J. 96:100–108.

Henderson, T.L., M.F. Baumgardner, D.P. Franzmeier, D.E. Scott, and D.C. Coster. 1992. High dimensional reflectance analysis of soil organic matter. Soil Sci. Soc. Am. J. 56:865–872.

Jackson, M.L. 1975. Soil chemical analysis– advanced course. M.L. Jackson, Madison, WI.

Johnson, R.J., P.G. Lucey, K.A. Horton, and E.M. Winter. 1998. Infrared measurements of pristine and disturbed soils 1. Spectral contrast differences between field and laboratory data. Remote Sens. Environ. 64:34–46.

Kilmer, V.J., and L.T. Alexander. 1949. Methods of making mechanical analysis of soils. Soil Sci. 68:1–24.

Kruse, F.A. 1988. Use of airborne imaging spectrometer data to map minerals associated with hydothermically altered rocks in the northern Grapevine Mountains, Nevada and California. Remote Sens. Environ. 24:31–51.

Mathews, H.L., R.L. Cunningham, and G.W. Petersen. 1973. Spectral reflectance of selected Pennsylvania soils. Soil Sci. Soc. Am. J. 37:421–424.

Matthias, A.D., A. Fimbres, E.E. Sano, D.F. Post, L. Accioly, A.K. Batchily, and L.G. Ferreira. 2000. Surface roughness effects on soil albedo. Soil Sci. Soc. Am. J. 64:1035–1041.

Odeh, I.O.H., A.B. McBratney, and D.J. Chittleborough. 1995. Further results on prediction of soil properties from terrain attributes: Heterotropic co-kriging and regression/kriging. Geoderma 67:215–225.

Salisbury, J.W., and D.M. D'Aria. 1992. Infrared (8–14 μm) remote sensing of soil particle size. Remote Sens. Environ. 42:157–165.

Shaw, J.N., D.W. Reeves, and C.C. Truman. 2003. Iron and Aluminum Clay mineralogy and dispersibility of soil and sediment derived from Rhodic Paleudults. Soil Sci. 168:168:209–217.

Shaw, J.N., C.C. Truman, and D.W. Reeves. 2002. Mineralogy of eroded sediments derived from highly weathered soils. Soil Tillage Res. 68:59–69.

Stoner, E.R., and M.F. Baumgardner. 1981. Characteristic variations in reflectance of surface soils. Soil Sci. Soc. Am. J. 45:1161–1165.

Sudduth, K.A., and J.W. Hummel. 1991. Evaluation of reflectance methods for soil organic matter sensing. Trans. Am. Soc. Agric. Eng. 34:1900–1909.

Thomasson, J.A., R. Sui, M.S. Cox, and A. Al-Rajehy. 2001. Soil reflectance sensing for determining soil properties in precision agriculture. Trans. Am. Soc. Agric. Eng. 44:1445–1453.

Triantafilis, J., W.T. Ward, I.O.A. Odeh, and A.B. McBratney. 2001. Creation and interpolation of the continuous soil layer classes in the lower Naomi Valley. Soil Sci. Soc. Am. J. 65:403–413.

Young, F.J., and R.D. Hammer. 2000. Defining geographic soil bodies by landscape position, soil taxonomy, and cluster analysis. Soil Sci. Soc. Am. J. 64:989–998.

Zamudio, J.A., and W.W. Atkinson. 1990. Analysis of AVIRIS data for spectral discrimination of geologic materials in the Dolly Varden Mountains, Nevada. p. 162–166. *In* Proc. The 2nd Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) Workshop, JPL Publication 90–54, Jet Propulsion Laboratory, Pasadena, CA.

Zhang, R., A.W. Warrick, and D.E. Meyers. 1992. Improvement of the prediction of particle size fractions using spectral indices. Geoderma 52:223–234.